# An automated severity classification model for diabetic retinopathy

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**Abstract -** *Diabetic Retinopathy (DR) - a complication developed due to heightened blood glucose levels- is deemed one of the most sight-threatening diseases. Unfortunately, an ophthalmologist, a process that can be considered incorrect and time consuming, manually acquires the DR screening. In view of the huge increase in diabetic patients over recent years, automated diagnostic tests for diabetes have also become an increasingly important research topic. Additionally, Convolutional Neural Networks (CNN) have proven themselves to be state-of-the-art for DR stage diagnosis in recent times. This study offers a fresh, automatically learning-based method for determining severity from a single Colour Fundus Photograph (CFP). The suggested method builds a visual embedding using DenseNet169's encoder.. Convolutional Block Attention Module (CBAM) is also added on top of the encoder to boost its ability to discriminate. The model is then trained using the Kaggle Asia Pacific Tele-Ophthalmology Society (APTOS) dataset using cross-entropy loss. In comparison to state-of-the-art performance on the binary classification test, we achieved (97% accuracy, 97% sensitivity, 98.3% specificity, and 0.9455, Quadratic Weighted Kappa score (QWK)). Additionally, for severity grading, Our network demonstrated high proficiency (82% accuracy - 0.888 (QWK)). The suggested approach makes a substantial contribution by accurately classifying the degree of diabetic retinopathy severity while requiring less time and spatial complexity, making it a promising contender for autonomous diagnosis.*

***Key Words***: Diabetic retinopathy, convolutional neural networks (CNN), attention mechanism, deep learning.

## 1.INTRODUCTION

Hyperglycemia, a symptom of the chronic metabolic disorder diabetes mellitus, has a long-term negative impact on the body's blood vessels on both a micro and macro level. The World Health Organisation (WHO) estimates that there were 422 million diabetics worldwide in 2014, and that figure is expected to rise to 700 million by 2045 [1], [2]. diabetes retinopathy, a progressive anomaly exposed and recognised through ocular pathologies, which results in blocking and bleeding of the retinal capillaries, is one of the long-term diabetes micro-vascular consequences. Fortunately, vision damage can be avoided by early identification. Without routine inspection, it could cause irreparable harm. According to the International Diabetes Federation (IDF), there are 93 million diabetics worldwide. Eye injury, but there are only 200,000 ophthalmologists in the globe [3]. Grading inconsistencies, a serious shortage of ophthalmologists in the field, as well as the problematic lab procedure, continue to be barriers to the early diagnosis of diabetic retinopathy. To lessen the heavy burden on healthcare systems, retinopathy tests should be automated. This has spurred major attempts to improve computer-aided medical diagnostics (CAMD) systems.

DR grading methods can be divided into two groups: separating diabetic retinas from healthy ones (binary classification problem) and determining the severity of afflicted retinas from class 0 (healthy) to class 4 proliferative DR (PDR) (multi-class classification task). Algorithms used for traditional machine learning (ML) are examples of artificial intelligence (AI) methods that gain knowledge by being exposed to data.

Gradient Boosted Trees (GBT) [6] as a classification model and Artificial Flora Algorithm (AFA) [5] for feature selection. Furthermore, by using the feature engineering method and Support Vector Machines (SVM) as a classifier for DR detection, Gharaibeh et al. took use of this in [7] and [8]. Despite their effectiveness, ML algorithms require individualised experience and subject expertise to find the most informative representation.

Through the representation of the universe as a layered hierarchy of concepts, each concept in Deep Learning (DL) has established a foothold in a variety of domains [10].

Utilising the capabilities of convolutional neural networks in the medical field has led to the development of more durable treatments, particularly in the DR sector. The efficacy of such a method for retinal vascular segmentation was shown in [16] and [17]. Similarly, Zhao et al. [18] were able to create fundus images using generative advertisement networks (GANs). For the early detection of Micro-aneurysms (MA), Dai et al. [19] used a multi-sieving convolutional neural network and picture to text mapping. [20] assessed the effectiveness of VGG16, VGG19, and InceptionV3 as three well-known CNN architectures. using transfer learning and adjusting for binary and multi-class classification [21, 22]. In order to categorise fundus images into two grades, Zeng et al. [23] proposed Siamese-like architecture [24] trained with transfer learning.

## 2.EXISTING SYSTEM:

Diabetic retinopathy (DR), a result of high blood glucose levels, is one of the disorders that poses the biggest danger to vision. Unfortunately, DR screening must be manually collected through an ophthalmologist, which is time-consuming & prone to error. An emphasis on automated DR diagnosis has emerged in recent years as a result of the dramatic increase in the number of diabetic patients. There are several existing systems for automated severity classification of diabetic retinopathy (DR) using different approaches. Some of the notable systems are:

"EyeArt" System: This system uses a machine learning algorithm to analyze retinal images and classify them into different severity categories. The system is designed to be user-friendly and requires minimal training to operate. It has been approved by the US Food and Drug Administration (FDA) for use in clinical settings.

"IDx-DR" System: This system uses an artificial intelligence algorithm to analyze retinal images and diagnose diabetic retinopathy. The system is fully automated and does not require a trained specialist to interpret the results. It has also been approved by the FDA for use in clinical settings.

"RetinaScope" System: This system uses a deep learning-based approach to analyze retinal images and classify them into different severity categories. The system is designed to be used by non-expert healthcare providers and can provide a diagnosis in under a minute. It has been tested in several clinical studies and has shown promising results.

"Google AI" System: This system uses a deep learning-based approach and has been developed by Google AI researchers. The system was trained on a large dataset of retinal images and achieved state-of-the-art performance on the DR dataset. It has not yet been approved for clinical use.

DLS-DR" System: This system uses a deep learning-based approach and has been developed by researchers at the University of Michigan. The system achieved an accuracy of 95.3% on the DR dataset and can classify retinal images into different severity categories. It has not yet been approved for clinical use.

In conclusion, there are several existing systems for automated severity classification of DR using different approaches, including machine learning and deep learning-based models. These systems have the potential to improve access to timely and accurate diagnosis of DR, which can help prevent vision loss and blindness in patients with diabetes. However, further validation and clinical trials are needed to ensure their safety and efficacy in real-world settings.

### 2.1.DISADVANTAGES OF EXISTING SYSTEM:

- Must manually gather DR screening
- Which takes time
- is prone to inaccuracy.

## 3.PROPOSED SYSTEM:

In this study, we examine the effectiveness of lightweight deep learning architecture considering quick & reliable diabetic retinopathy severity rating. Our system is built on a modified version of Dense Net that incorporates an attention mechanism considering further feature refinement. Additionally, we analyze how data imbalance affects model performance & employ an imbalanced learning strategy to counteract it.

### 3.1ADVANTAGES OF PROPOSED SYSTEM:

1. For severity grading, our network demonstrated great competency.

2. The suggested framework makes a substantial contribution through effectively grading the degree of diabetic retinopathy severity while requiring less time & space complexity, making it a feasible option considering autonomous diagnosis.

## 4.SYSTEM REQUIREMENTS:

The functional needs of the application are further described in this section. The SRS can be broken down into modules, each of which has specifications. The following hardware & software are need to complete the project.

## 5.HARDWARE REQUIREMENTS:

- Hard Disk : 40GB
- Floppy Drive : 1.44MB
- Monitor : 15VGACOLOUR
- RAM : 512MB

### 5.1SOFTWARE REQUIREMENTS:

- Python IDE 3.7 version (or)
- Anaconda 3.7 (or)
- Jupyter (or)
- Google Collaboratory

## 6.CONVOLUTIONAL NEURAL NETWORK:

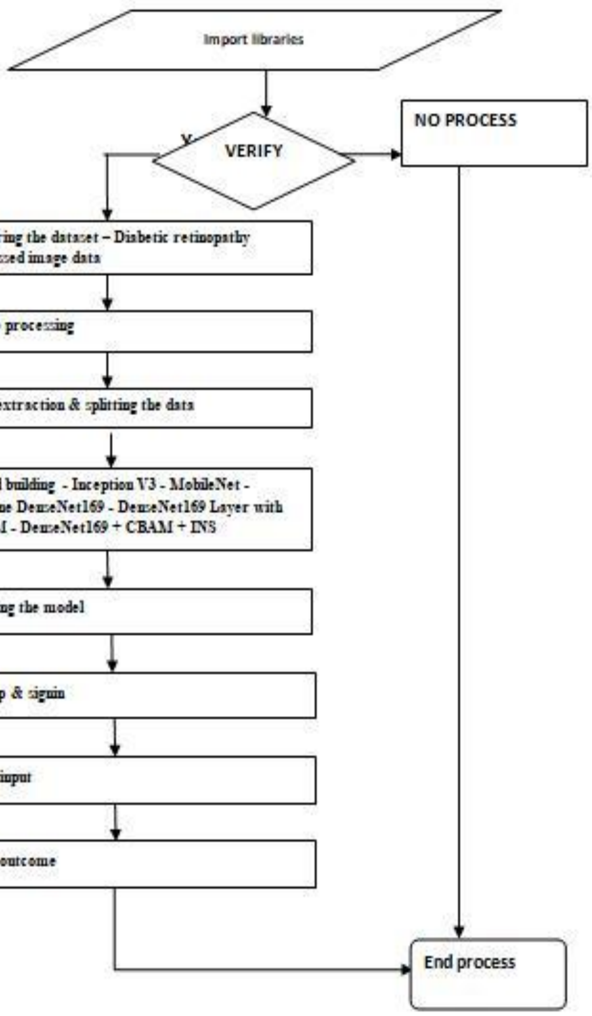
- Convolution neural network is mainly used for applications in image and speech recognition as its built-in convolutional layer reduces the high dimensionality of images without losing its information.

- Convolutional Neural Network (CNN) is the most popular deep learning framework

- CNN is one of the best architectures that can process these images and implement the proposed architecture.

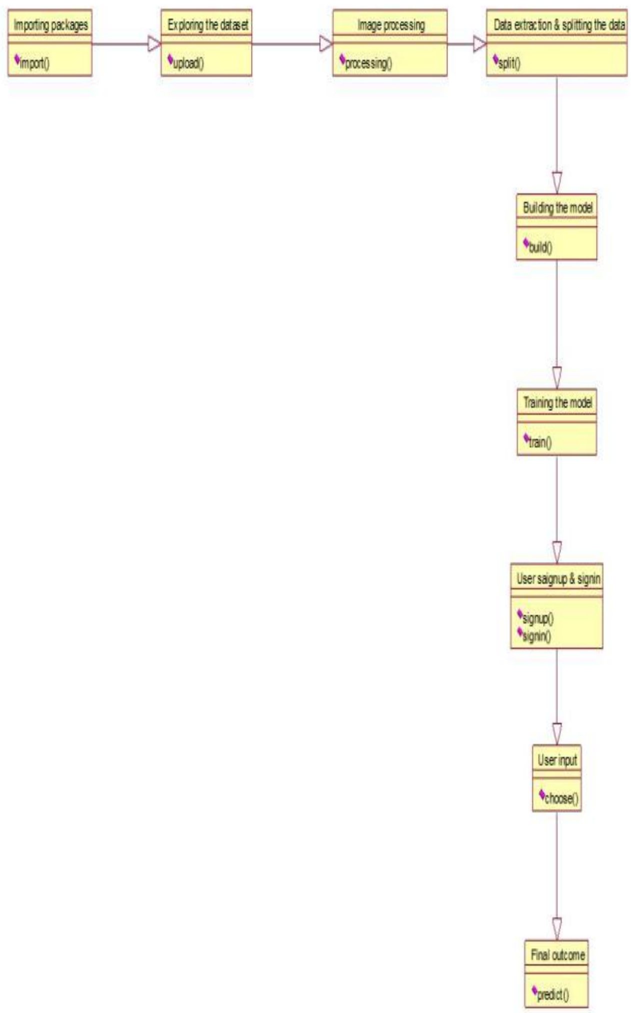
## 7.DATA FLOW DIAGRAM:

The DFD is alluded to as an air pocket outline too. A direct graphical formalism might be utilized to portray a framework as far as information that is taken care of into it, various tasks that are performed on it, & information that is delivered because of those tasks.




## 8. CLASS DIAGRAM FOR DIABETIC RETINOPATHY:

The class chart is utilized to clean utilize case outline & indicate a careful framework plan. use case graph's entertainers are ordered into various interconnected classes utilizing class chart. It is conceivable believing there to be a will be a or has-a interface between classes. Different functionalities may be accessible from each class in class outline. These highlights presented through class are known as its "techniques." likewise, each class could have specific "credits" that explicitly recognize class.



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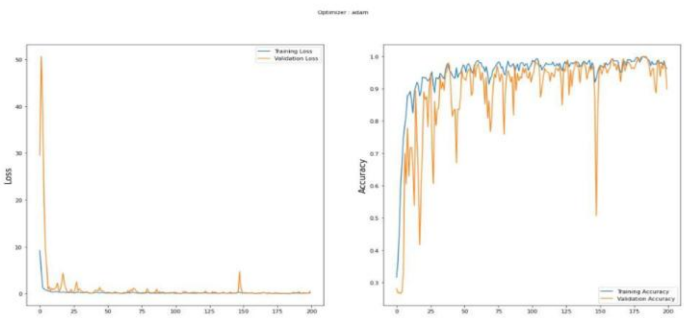
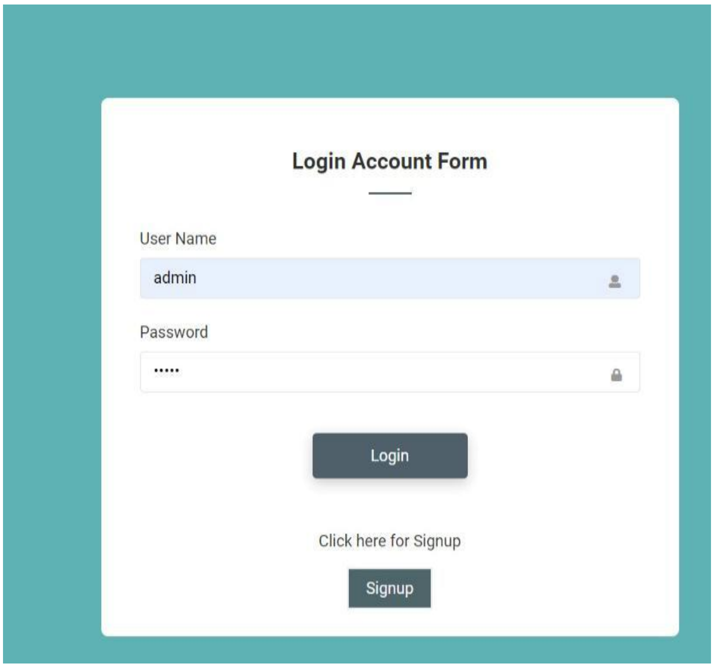
```
[10]: import matplotlib.pyplot as plt

x=r1
plt.figure(figsize=(20,10))
plt.subplot(1, 2, 1)
plt.suptitle('Optimizer : adam', fontsize=10)
plt.ylabel('Loss', fontsize=16)
plt.plot(x.history['loss'], label='Training Loss')
plt.plot(x.history['val_loss'], label='Validation Loss')
plt.legend(loc='upper right')

plt.subplot(1, 2, 2)
plt.ylabel('Accuracy', fontsize=16)
plt.plot(x.history['accuracy'], label='Training Accuracy')
plt.plot(x.history['val_accuracy'], label='Validation Accuracy')
plt.legend(loc='lower right')
plt.show()
```

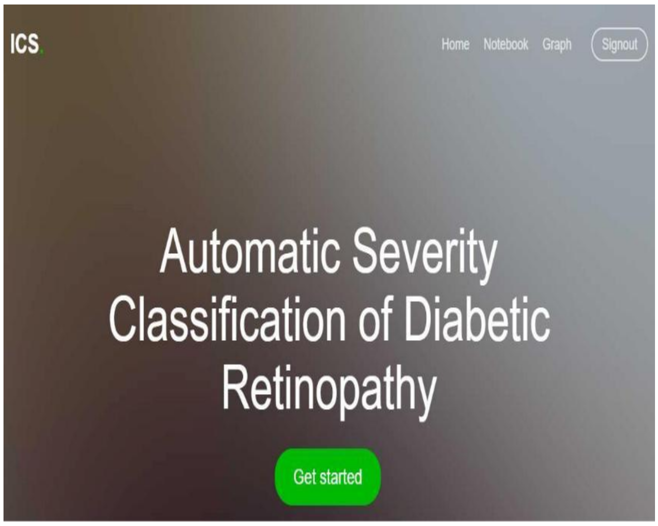



Showing the loss and accuracy in the form of graphs

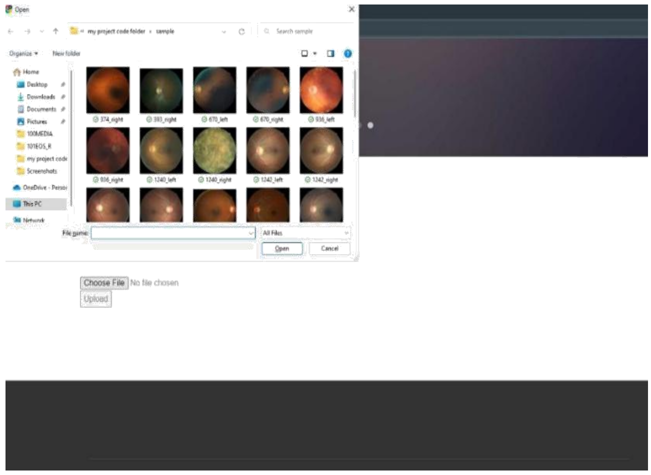
## 11 RESULTS AND DISCUSSIONS



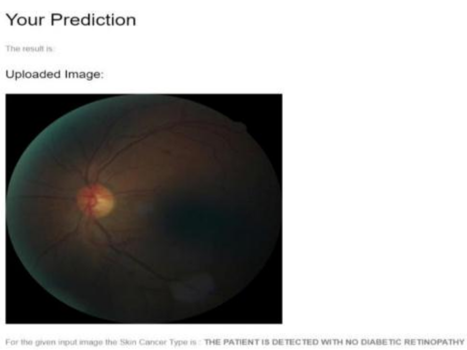

Login into the account and give registered details




Home page is opened



Choose file from the folder and select an image and upload the image.




After uploading your prediction is shown here so here the patient severity condition is detected with no diabetic retinopathy

## 12.CONCLUSIONS

In this study, we took advantage of a novel CNN model built on the DenseNet169 architecture & coupled among CBAM as a supplement to be added considering improving representational power. The suggested approach reduced the burden of space & time complexity while demonstrating solid performance & comparable quality criteria. A 2-D Gaussian filter also improves the quality of fundus photographs. Finally, in order to address the class imbalance & enhance the model's ability to forecast across all classes, we employed INS to create our weighted loss function. We compare the effectiveness of several CBAM configurations considering future research directions. Additionally, expanding the dataset size & experimenting among various unbalanced learning algorithms will result in improved performance.

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